Disaster Resilience: Government Responses and Default Risk Around the World

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Abstract

We examine how government responses to the global crisis influence default risk. Using a large sample of firms across 107 countries, we find that default risk increases with stringency levels of government responses to COVID-19. The government's financial support and societal trust moderate the effects of the government's responses on firm default probability. While more stringent government responses to the pandemic initially result in a greater degree of default risk, these responses later benefit firms' solvency. Overall, our findings have valuable implications for crisis management practices and policies mitigating the adverse impacts of disaster incidences on financial markets.

Keywords: disaster risk; default risk; government response; crisis management practice.

Data availability: The data are available from the sources identified in the paper.

"*The first role of government is to help people who are in crisis or need. That's why we have government.*"
– John McCain, Former United States Senator and Member of the House of Representatives.

1. Introduction

Since the start of the millennium, the world has gone through several severe crises, such as the dot-com bubble, the 2008 financial crisis, and most recently, the Coronavirus pandemic. Such global extreme events have made corporate insolvency and creditworthiness among the most attention-grabbing issues in financial markets.[1, 2] As default is one of the most unfavorable outcomes in the life of a corporation (Brogaard, Li, and Xia, 2017) and involves multi-dimensional costs of default (Davydenko, Strebulaev, and Zhao, 2012), an extant literature has been dedicated to examining how a firm-level attribute or a country's institutional backgrounds affect credit risk assessment (e.g., Feder and Ross, 1982; Cosset and Roy, 1991; Bharath and Shumway, 2008; Avramov, Chordia, Jostova, and Philipov, 2012). However, how government responses to hazardous events contribute to corporate resilience remains under-investigated.[3] This paper addresses this inconvenience void by examining the extent to which the government responses to a global crisis affect firm-level default risk.

Our focus on the government responses to global crises is motivated by the roles of politics on financial market outcomes (e.g., Santa-Clara and Valkanov, 2003; Bonaparte and Kumar, 2013; Blinder and Watson, 2016) and an extant political science literature on political inventions into markets in times of crisis (e.g., Rosas, 2006; Pontusson and Raess, 2012). We

[1] See, for example, Vassalou and Xing (2004), Campbell, Hilscher, and Szilagyi (2008, 2011), Duchin, Ozbas, and Sensoy (2010), Giesecke, Longstaff, Schaefer, and Strebulaev (2011), Longstaff, Pan, Pedersen, and Singleton (2011), Beltratti and Stulz (2012), Brogaard, Li, and Xia, 2017; Aretz, Florackis, and Kostakis (2018), Frick (2019); Martinez, Zouaghi, Marco, and Robinson (2019), and Wenzel, Stanske, and Lieberman (2020).
[2] Figure A1 that reports the number of media mentions on "corporate default" from Factiva suggests that since 2010, default risk is mentioned in the media more than 100 times higher than in 1990s.
[3] Default risk generally refers to the likelihood that a firm is not able to fulfill its debt obligations (Garlappi, Shu, and Yan, 2008).

utilize the recent COVID-19 pandemic as our research setting for two reasons. First, unlike prior crises, the pandemic has a more abrupt effect on the world economy and requires global immediate and decisive government actions. For example, governments have undertaken lockdown measures to prevent the spread of the virus, such as school closings, travel restrictions, bans on public gatherings, and contact tracing. Such non-economic responses can have substantial social and economic impacts on communities (Wenzel, Stanske, and Lieberman, 2020; Brodeur, Clark, Fleche, and Powdthavee, 2021; Müller and Rau, 2021). Second, there have been wide variations in how governments across countries respond to the pandemic, both in the adopted measures and implementation timing (Hale *et al.*, 2020). These variations are ideal for us to comprehensively assess the role of the government's crisis responses to firm insolvency.

While economic policies are essential in hard times (Gourevitch, 1986), the magnitude, frequency, and various forms of political intervention in times of crisis remain heated debate topics for both academics and practitioners (e.g., Pontusson and Raess, 2012). Regarding the recent COVID-19, the confinement measures implemented across countries can achieve their purpose in curbing the virus's spread. These approaches, however, can impose a high toll on economic activities. Notably, the dramatic change in consumption patterns and sudden disruption to business operations has impaired company cash generation, leaving firms with considerable challenges to meet their debt obligations. We, therefore, conjecture that the more stringent the government response to combat the virus, the more insolvent a firm becomes.

Empirical results support our hypothesis. In a large sample of 21,978 firms across 107 countries, we find that firms located in a country with more stringent government responses to the health crisis have a higher probability of being insolvent in the first two quarters of 2020 since the pandemic struck. To address endogeneity concerns, we adopt four identification approaches. First, we use firm-fixed effects, country-fixed effects, and time-fixed effects to account for firm-, country-, and time-invariant factors that could be associated with default risk. Second, we employ a multivariable matching approach to mitigate concerns that observable firm characteristics drive our results. Third, we exploit a neat comparison pair of Norway and Sweden, two countries with very similar features except for their different strategies in responding to the COVID-19 pandemic. Applying the difference-in-differences approach, we find that firms in Norway, the country with more intense lockdown measures, face a higher risk of default than those in Sweden, which adopts a more lenient approach to handle the pandemic. Forth, we consider a number of alternative measures of government response to crises and default risk to ensure that our documented findings are not sample-specific. We consider nine different metrics of the government stringency index and find that each of the nine components contributes to the likelihood of corporate default. In addition, we employ credit default swap (CDS) spread as a market-based indicator of default risk and document a significantly higher CDS spread among firms in countries with the most stringent preventive measures than those in the least restrictive ones.

We further examine the underlying mechanisms through which government response to crises can influence firm default probability as a fundamental channel mitigates spurious estimations (Siegel, 2016). We find that lower profitability, cash reserves, and inability to pay suppliers or creditors channel the lockdown measures' adverse effects into corporate default.

To further our understanding of the effects of governments' responses on corporate insolvency, we inspect the nature of this effect across different institutional settings. We find that, in countries where the COVID-19 situation is acute, more stringent control measures help reduce corporate default likelihood. In addition, the government's economic support can effectively alleviate the lockdown measures' adverse consequences on default risk. As trust in the government and community mitigates the breaching of lockdown rules and improves the effectiveness of governments' responses, we document that the negative impacts of the

COVID-19 control measures are lessened in countries with high societal trust. Finally, we investigate the time-series variation in how government response stringency affects corporate insolvency. We find that more extreme control measures at the early stage of the pandemic are conducive to longer-term benefits in reducing corporate default risk in subsequent periods.

Our study makes several contributions to the literature. First, our paper contributes to a growing body of studies that document the roles of politics on financial market outcomes. Santa-Clara and Valkanov (2003), for example, show that stock market returns are higher under Democratic than Republican presidencies. Pástor and Veronesi (2020) develop a model of political cycles that explain the presidential puzzle as documented in Santa-Clara and Valkanov (2003). Bonaparte and Kumar (2013) find that greater political activism increases the stock market participant rate. Blinder and Watson (2016) suggest that the economy performs better under Democratic than Republican presidencies, while Marshall, Nguyen, Nguyen, and Visaltanachoti (2018) show that the equity market is more liquid when Democratic presidents are in power. Nagar, Schoenfeld, and Wellman (2019) document that government economic uncertainty matters for a corporate information environment. Our study utilizing the global pandemic setting suggests that firm default risk increases with the stringency levels of government responses to COVID-19.

Second, our paper extends a growing body of research that advances our understanding of the adverse impacts of disaster incidences on the health of people and various economic outcomes (e.g., Altig *et al.*, 2020; Bargain and Aminjonov, 2020; Pástor and Vorsatz, 2020; Brodeur, Clark, Fleche, and Powdthavee, 2021; Campos-Mercade, Meier, Schneider, and Wengström, 2021; Goolsbee and Syverson, 2021; Hensvik, Le Barbanchon, and Rathelot, 2021). More recently, Foley, Kwan, Philip, and Ødegaard (2022) find that a WHO's declaration of COVID-19 pandemic triggers the liquidity crisis. We show that government responses to the crisis influence firm survival in an international setting. Our paper is also related to a strand of studies that investigate the drivers of business reliance in times of crisis.[4] We find that while highly stringent government responses to the pandemic result in a greater degree of corporate default risk in the short run, these responses are beneficial to firms' solvency in later periods.

Third, this study contributes to the stream of research on the determinants of default risk (e.g., Bharath and Shumway, 2008; Campbell, Hilscher, and Szilagyi, 2008; Giesecke, Longstaff, Schaefer, and Strebulaev, 2011; Aretz, Florackis, and Kostakis, 2018). While a majority of previous studies documenting the determinants of default risk in the U.S. market (e.g., Brogaard, Li, and Xia, 2017; Giesecke, Longstaff, Schaefer, and Strebulaev, 2011; Goyal and Wang, 2013), our paper provides a comprehensive investigation of firm-level default risk in a global setting with over 100 countries with various institutional and regulatory features.

Forth, our study uncovers government policies' economic outcomes in times of crisis (e.g., Pontusson and Raess, 2012; Bargain, and Aminjonov, 2020; Blanton, Blanton, and Peksen, 2015; Ha and Kang, 2015; Pulejo and Querubín, 2021). Our study adds to the debate that has drawn significant attention from policymakers and the public on the appropriate degree and timing of government interventions amid extreme events. Furthermore, our study serves a wide range of audiences since research on government responses to disastrous incidences and default risk have been of particular interest to scholars in finance and other inter-disciplinary research (e.g., economics, accounting, management). We respond to Buckley, Doh, and Benischke's (2017) call to expand the impacts of cross-country studies and address the current issues in financial markets. Our findings carry important implications on crisis management practices and policies to ease the consequences of disastrous incidences and build business resilience during major disruptions from a practitioner's perspective.

[4] See, for example, Beltratti and Stulz (2012), Lins, Servaes, and Tamayo (2017), Albuquerque, Koskinen, Yang, and Zhang (2020), Baker *et al.* (2020), Ding, Levine, Lin, and Xie (2021), Fahlenbrach, Rageth, and Stulz (2021), Li, Liu, Mai, and Zhang (2021).

2. Literature Review and Hypothesis Development

2.1. Government responses in crisis

Government intervention is a common practice, and its effects on international business have been studied extensively in the literature (see, for example, Litvak, 1986; Guisinger, 1989; Brewer, 1993; Wang, Hong, Kafouros, and Wright, 2012). The impacts of government involvement have become even more heated in the context of global disasters. Previous studies in business, finance, and management literature mainly focus on crisis management policies for economic crises. In the past few decades, the world has witnessed an increasing number of devastating "non-economic" events with global reaches, such as terrorist attacks, natural catastrophes, and disease outbreaks. Investigating the impacts of government responses to the business sectors during non-economic crises is often more challenging because government interventions in these cases include both economic and non-economic measures. The recent COVID-19 pandemic provides a telling example. The pandemic has urged governments globally to adopt various economic and social interventions to contain the coronavirus and its consequences.

Keeping businesses viable and stabilizing the economy is among the governments' critical goals during a crisis since corporate solvency issues could spill over to the financial sector and eventually hurt the whole economy. During the COVID-19 pandemic, governments across nations face the dilemma of applying social distancing measures to curb the outbreak or keeping businesses open to avoid economic disruptions, especially to firms' liquidity and solvency.

2.2. Government responses to the pandemic and corporate default

The COVID-19 pandemic provides a natural platform to study corporate insolvency risk at a cross-country level as it has gravely wounded the global economy. The government's strict control measures to combat the outbreak can cause disruptions in supply chain and business operations, thereby deteriorating firms' revenue generation. Firms can face severe financial distress and a higher probability of default as a result. We, therefore, propose our first hypothesis as follows:

Hypothesis 1: *More stringent government responses to the pandemic are associated with higher default risk.*

The wide variations in COVID-19 protective measures across countries enable us to investigate government interventions' effects on corporate default cross-sectionally. We argue that in countries where the pandemic is more severe, extreme control measures are necessary, and their benefits will outweigh the adverse impact of the interventions on default risk, which leads us to our second hypothesis:

Hypothesis 2A: *The effect of government stringency response on default risk is weaker in countries where COVID-19 is more severe.*

Apart from non-economic measures, governments have also adopted economic policies that assist businesses struggling amid the coronavirus outbreak, such as the introduction of stimulating packages and financial supports. We posit that such governments' economic interventions relieve pressure on the business sector's insolvency and reduce default probability. To test this proposition, we put forward another hypothesis as below:

Hypothesis 2B: *The effect of government stringency responses on default risk is weaker in countries with more financial support from the government.*

The variations in legal mechanisms in creditor protection across countries can also affect corporate insolvency because strong creditor protection induces pressure on firms to meet their debt obligations (e.g., Aretz, Florackis, and Kostakis, 2018; Garlappi, Shu, and Yan, 2008). Thus, we expect that the adverse impact of stringent government intervention on default risk is more pronounced for firms in countries with higher creditor protection. This leads to the following hypothesis:

Hypothesis 2C: *The effect of government response on corporate default is more pronounced in countries with strong credit protection.*

Besides these aspects, social trust constitutes a valuable intangible asset for individuals, societies, and their governments, especially during the challenging time of the COVID-19 pandemic. As trust is a fundamental factor in crisis management (Sapienza and Zingales, 2012), we expect higher regulatory compliance in countries with higher social trust. Hence, the government control measures are most likely effective in containing the pandemic. Furthermore, given trust can help ease access to financing (Thakor and Merton, 2018), we expect that the negative impact of strict lockdown measures on firm insolvency will diminish in countries with higher social trust. We propose the following hypothesis:

Hypothesis 2D: *The effect of government stringency responses on default risk is less pronounced in countries with higher social trust.*

Lastly, we examine whether high and low government response stringency carry differential effects on corporate default risk over time when facing the same level of COVID-19 severity. We anticipate that stringent government responses can be necessary for the long run as pre-emptive measures seem to contain the outbreak faster, increasing the chance to save the economy. Our final hypothesis is as follows:

Hypothesis 3: *Firms in countries with more stringent government responses to the pandemic have lower default risk in later periods.*

3. Data and Sample

3.1. The Stringency of Government Responses to COVID-19

This study adopts Hale *et al.*'s (2020) country-level COVID-19 response stringency index to measure how stringent government responses are in the fight against the pandemic. The index is constructed based on nine different metrics, including (i) restrictions on internal movement; (ii) international travel controls; (iii) public information campaigns; (iv) cancellation of public events; (v) restrictions on public gatherings; (vi) public transport closures; (vii) school closures; (viii) stay-at-home orders; and (ix) workplace closures. The government response stringency index is a simple average of the nine component indicators, each taking a value between 0 and 100. We compute the government response stringency variable (*GSI*) as the mean value of the daily response stringency scores within each month. A higher *GSI* value indicates that the government imposes stricter policies in a given month to tackle the pandemic.

3.2. Default Risk Measures

We employ Merton's (1974) distance-to-default (*DTD*) to measure default risk for two reasons. First, Merton's (1974) approach is a widely used market-based measure of default risk and outperforms accounting-based estimation of default risk (e.g., Bharath and Shumway, 2008; Campbell, Hilscher, and Szilagyi, 2008; Das, Hanouna, and Sarin, 2009; Brogaard *et al.*, 2017). Second and more importantly, the measure of *DTD* is implementable in an international setting (e.g., Zhang, Ouyang, Liu, and Xu, 2020; Nadarajah *et al.*, 2021; Kabir, Rahman, Rahman, and Anwar, 2021), which facilitates our cross-country research on the impact of government responses to the crisis.

We obtain the monthly *DTD* measure from the Credit Research Initiative (CRI) database built on the forward intensity model developed by Duan, Sun, and Wang (2012) for multiperiod default prediction.[5] The estimation model is as follows:

$$DTD = \frac{\ln(\frac{V_t}{L})}{\sigma\sqrt{T-t}} \tag{1}$$

where the default point L = current liability + (0.5 × long-term liability) + (δ × other liability), and δ is specified and estimated for sectors in each calibration group.[6] The higher the distance-to-default (*DTD*) value, the larger the positive spread between firm value and firm liabilities, and the lower the probability of default.

Following Bharath and Shumway (2008) and Brogaard, Lia, and Xia (2017), we use the cumulative normal distribution of the negative distance-to-default (denoted *EDF*) as an alternative measure of default risk.

3.3. Sample and Descriptive Statistics

This study gathers data from several data sources. The government response stringency index (GSI) is obtained from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale *et al.*, 2020). Default risk data is from the CRI database. Stock return and accounting data are from CRSP/Compustat Global. Country characteristics are from several public data sources, such as the World Value Survey database and Djankov, Hart, McLiesh, and Shleifer (2008)'s survey on creditor protection. To construct our sample, we start with the intersection

[5] Duan *et al.* (2012) provide comprehensive evidence suggesting that this method of estimating *DTD* outperformance the traditional destination technique. We thank the Risk Management Institute (RMI) of the National University of Singapore for generously providing the CRI database.

[6] See Duan *et al.* (2012)'s Appendix B for the details of the estimation process.

of the aforementioned databases. The final sample covers 246,454 observations for 21,978 firms in 107 countries from July 2019 to June 2020, the latest data at the time of writing.

Appendix 2 reports the summary statistics for each country in our sample. Overall, Appendix 2's results suggest an increase in default risk, as measured by distance-to-default and expected default frequency, between 2019 and 2020 across countries, consistent with an exogenous rise in expected default frequency caused by the COVID-19.

Table 1 presents the descriptive statistics for our main variables (Panel A) and Spearman's rank correlation between these variables (Panel B). On average, the stringency of government response to COVID-19 across 107 countries is 18.811. For two default risk measures, the sample mean of *DTD* and *EDF* measures are 3.970 and 0.051, respectively.

Spearman's rank correlation results in Table 1's Panel B suggest strong correlations between the two default risk measures (i.e., distance-to-default and expected default frequency). More importantly, the stringency level of policy responses to COVID-19 is negatively correlated with the distance-to-default measure while positively correlated with expected default frequency, thereby corroborating our first hypothesis (H1). However, some of the differences in default risk could be due to time-, industry-, or firm-invariant factors, which we will consider in the following sections.

[Insert Table 1 here]

4. Results and Discussions

4.1. Univariate Analysis

We present preliminary evidence of the association between the government response stringency and corporate default risk using a nonparametric approach in Panel A of Table 2. To conduct a univariable analysis, we first rank firms into quintiles based on the government response stringency index (*GSI*) during the first 6 months of 2020. Firm-month observations assigned to the fifth quintile face the most stringent lockdown measures, whereas those in the first quintile are the least restricted. We then perform univariate tests for the firm-months in each quintile and compare their likelihood of default in 2020 to that shifted backward to 2019 within a six-month window. For instance, if a firm's default risk measures are as of April 2020, we compare these values to those backdated in October 2019.

We document significantly higher default risk among firms in the fifth quintile than those in the first quintile over the first six months of 2020, as shown in columns (1) and (2) of Panel A, providing supportive evidence for our hypothesis 1. In columns (3) and (4), the difference between these two extreme quintiles goes in the reverse direction: firms located in the most stringent areas were less likely to default six months before the pandemic. These results underpin the unprecedented business interruptions due to the "black swan" event of COVID-19, which results in exceptional corporate default risk.

4.2. Regression Analysis

We extend our analysis to a multivariate setting where we can control for industry-specific characteristics and time-invariant factors at the same time. We estimate the ordinary least squares (OLS) regression as specified below:

$$Default\ Risk_{i,j,t} = \beta_0 + \beta_1 \times GSI_{j,t-1} + Z_{i,t-1}, + CountryFE + IndustryFE + TimeFe + \varepsilon_i \qquad (2)$$

where *i* and *t* subscript firm and month, respectively. *Default Risk* represents two alternative default risk measures. *GSI* is the monthly government response stringency index. *Z* is the vector of control variables. Following the literature on default risk (e.g., Bharath and Shumway, 2008; Brogaard *et al.*, 2017; Nadarajah *et al.*, 2021), we control for various firm-level characteristics that can be associated with corporate default, including firm size (*Size*), cash-to-assets ratio (*Cash*), return on assets (*Profitability*), the book value of debt to assets (*Leverage*), monthly excess stock return (*Return*), and Amihud's (2002) measure of illiquidity (*Illiquidity*). The accounting controls are estimated at the most recent fiscal quarter. Detailed definitions of these variables are presented in the Appendix. We include the country-fixed effects, industry-fixed effects (based on two-digit standard industry classification (SIC)), and calendar quarter-year to control the heterogeneity in firms' default risk across countries and industries. To correct for cross-sectional and time-series dependence, we use robust standard errors clustered simultaneously by both firm and quarter dimensions (Petersen, 2009; Gow, Ormazabal, and Taylor, 2010; Thompson, 2011).

The estimation results of Equation (2) are displayed in Table 2 Panel B. Regardless of model specifications, we find that the coefficient estimates of *GSI* are significantly negative in the *DTD* regressions while being positive and statistically significant in the *EDF* regressions. In terms of economic significance, the coefficients of *GSI* in columns (3) and (6) imply that a one-standard-deviation increase in the stringency index is associated with a 5.06% decrease in *DTD* and an 11.59% increase in *EDF* relative to their means.[7] These results suggest that the more stringent government responses to the COVID-19 pandemic are associated with a higher probability of corporate insolvency.

Consistent with prior studies (e.g., Ashbaugh-Skaife, Collins, and LaFond, 2006; Bharath and Shumway, 2008; Bonsall, Holzman, and Miller, 2017; Brogaard *et al.*, 2017; Cornaggia, Krishnan, and Wang, 2017; Nadarajah *et al.*, 2021), default risk is less pronounced for larger firms, firms with higher cash over asset ratio, firms with higher profitability and stock returns while higher for firms with higher leverage and firms with less liquid stocks.

[Insert Table 2 here]

[7] The economic significance is computed based on the coefficients of *GSI* (-0.0068 for *DTD* and 0.0002 for *EDF*) multiplied by the standard deviation of *GSI* (29.567) from Table 2, then divided by the mean values of *DTD* (3.97) and *EDF* (0.051), respectively.

As the government stringency index is constructed from nine different metrics, we further explore whether one measure may have a more significant impact than the others. We rerun our baseline models (Equation 2) when each of the nine metrics is the independent variable of interest and report the results for these tests in Table 3.

Results from Table 3 show that each of the nine components contributes to the likelihood of corporate default. Among the nine indicators, the effects of public event cancellations, workplace closures, public information campaigns, stay-at-home orders, international travel controls, and internal movement restrictions on corporate insolvency are more potent than the other measures.

[Insert Table 3 here]

4.3. Cross-Sectional Analyses

To gain more insights into the effects of governments' COVID-19 responses on corporate default risk, we examine how these effects vary across countries with divergent COVID-19 circumstances and social and institutional settings.

4.3.1. COVID-19 Severity

We argue that the benefit of the COVID-19 responses could prevail in countries where the COVID-19 situations are growing dire and social lockdowns are necessary to circumvent future economic contraction. To test this prediction, we introduce two country-level proxies for COVID-19 severity, including (*i*) the monthly increase in confirmed COVID-19 cases, scaled by population (denoted *COVID-19 Cases*), and (*ii*) the monthly increase in COVID-19-related deaths, scaled by population (denoted *COVID-19 Deaths*). We then include the interaction terms between *GSI* and COVID-19 severity measures into our baseline Equation (2).

The results from Panel A Table 4 corroborate Hypothesis 2A. First, the antagonistic relationship between the government response stringency index and corporate default risk persists after controlling COVID-19 severity. Second, the results show that firms located in countries that suffer more cases or deaths of COVID-19 are more likely to default. Intriguingly, all the coefficients on the interactions between GSI and the severity measures exhibit opposite signs and are greater in absolute value than those on GSI. These findings reveal that social lockdowns' marginal economic benefit outweighs its marginal cost and lowers the likelihood of corporate default in distinguished circumstances where government interventions are necessary.

We further examine how the impact of the government responses index on corporate default varies across industries. According to S&P Global Market Intelligence, we construct an indicator, *Industry At Risk*, indicating firms from five sectors most impacted by COVID-19. We report the results for these tests in Panel B of Table 4. Overall, Panel B's results suggest that the effects of government responses on corporate default are more pronounced among industries that are more exposed to the pandemic.

[Insert Table 4 here]

4.3.2. COVID-19 Government Support

Government support is essential in times of crisis. In this subsection, we test our hypothesis 2B that firms are less likely to default due to social lockdown in countries where governments are more financially supportive.

We exploit two different economic response measures, including (i) income support for people who lose their jobs or cannot work (*Income Support*) and (ii) freezing financial obligations for both households and firms (*Debt Relief*).[8] We augment our baseline regression in Table 3 with additional interaction terms between *GSI* and these two economic response

[8] According to OxCGRT database, each measure represents the ratings from 0 to 2, where a higher value indicates more economic support from the government.

measures. The results, reported in Panel A of Table 5, show that the government's financial support can help counteract the negative impact of the lockdown measures on default risk to a certain extent, which is consistent with the notion that government interventions keep businesses viable throughout the unfolding COVID-19 crisis. These results are also compatible with our Hypothesis 2B.

[Insert Table 5 here]

4.3.3. Creditor Protection

Under Hypothesis 2C, we expect countries where the bankruptcy code is more favorable to lenders to have a higher likelihood of default during the COVID-19 lockdowns. Using debt enforcement indicators from Djankov *et al.*'s (2008) survey, we follow Favara, Schroth, and Valta (2012) and construct two variables related to the strength of creditor protection. The first measure is the creditors' recovery rate (denoted *Recovery*). A higher value of recovery rate indicates a lower expected loss and a shorter time for a creditor to get paid in the event of default. The second measure is the renegotiation failure index (*RFI*), which summarizes the legal characteristics that protect debtholders from shareholders' strategic default; a higher value of *RFI* suggests stronger protection of creditors' rights. The interaction terms between *GSI* and these two proxies for creditors' rights capture the cross-country variation in the *GSI* effect. We report the results for these tests in Panel B of Table 5.

Consistent with our conjecture, we find that the adverse impacts of *GSI* on corporate default risk are more pronounced when firms are located in countries with higher protection of creditors' rights, as shown in Panel B of Table 5. These findings also provide evidence that lenders are in a panic mode, with concerns about how long the pandemic lasts and its economic consequences. Results from Table 5's Panel B support Hypothesis 2C.

4.3.4. Social Trust

In this subsection, we empirically test Hypothesis 2D, that high social trust induces coordinated responses in times of crisis and reduces financial instability triggered by the government's measures. We introduce two different measures of social capital. The first measure captures the country-level public trust in governments, following Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018) (denoted *Government Trust*). The second measure is the index of people's trust in other members from the same society available on the World Value Survey database (denoted *TrustOthers*). Higher values of both measures imply higher social trust. We then include the interaction terms between *GSI* and social trust measures into our baseline Equation (2) and report the results for these tests in Panel C of Table 5.

The estimated coefficients on the interaction terms between *GSI* and the two social trust measures are positive in the *DTD* regressions and negative in the *EDF* regressions. They are mostly statistically significant, except that shown in column (4) of the Panel. Overall, these results suggest the vital role of government and societal trust in moderating the unpleasant impact of the government's responses on firm solvency. Results from Table 5's Panel C corroborate Hypothesis 2D.

4.4. Identification Strategy

We employ several identification approaches to address potential endogeneity concerns. First, to ensure that our results are not driven by firm-invariant factors that could be associated with credit risk, we use firm-fixed effects along with country- and time-fixed effects. We report the results for these tests in columns (1) and (2) in Panel A of Table 6. The results consistently suggest that the more stringent government responses to the COVID-19 pandemic are associated with a higher probability of corporate insolvency.

Second, we adopt the multivariable matching approach (entropy balancing) developed by Hainmueller (2012). The entropy balancing approach overcomes several drawbacks of the propensity score matching method, such as its statistical inferences being less sensitive to design choices, and is well-employed in recent studies (e.g., Bonsall and Miller, 2017; Wilde, 2017; Joshi, 2020; McMullin and Schonberger, 2020). We re-estimate our baseline regression in Equation (2) using post-entropy balancing weights, and α_1, the parameter of interest, captures the influence of *GSI* on the likelihood of being insolvent. We report the results for these tests in columns (3) to (4) in Panel A of Table 6. We find our results are robust.

Third, to address potential omitted variables, we apply a difference-in-differences approach to investigate a pair of neighboring countries that adopt different strategies to handle the pandemic. They are Norway and Sweden. On March 12, 2020, Norway was among the first European countries to impose a national lockdown to curb the spread of COVID-19. On the other hand, Sweden took a more lenient approach, allowing large parts to remain open. While Norway and Sweden are similar across a vast number of societal aspects, the stark differences in their policy responses toward controlling the pandemic represent a natural setting to establish the effect of a national lockdown on corporate default risk.

We first conduct a nearest neighbor matching contingent on the propensity to be a Norwegian firm. We match a Norwegian firm with its most comparable Swedish firm based on their default risk and all other variables in Equation (2) from July 2019 to February 2020. As a result, matched firms within a pair are subject to a similar default risk level and other characteristics before the Norwegian lockdown implementation in March 2020. The national lockdown lasted until the Norwegian government began to ease their pandemic-related restrictions from April 24, 2020. We create an indicator variable *Lockdown,* which takes the value of 1 for Norwegian and Swedish firms from March 2020 to April 2020, and 0 during other periods. We generate an indicator, *Norway*, that equals 1 for Norwegian firms and 0 for

Swedish firms. Our variable of interest is the interaction term between *Norway* and *Lockdown*. Panel B of Table 6 presents the results of the test.

In column (1) of Panel B, where *DTD* is the default risk measure, the negative and significant difference-in-difference estimator *Norway×Lockdown* indicates that Norwegian firms experience a considerable decrease in the distance-to-default (*DTD*) during the implementation of the national lockdown. Compared to Swedish firms, Norwegian peers face a 7% decline in the average level of distance-to-default during the lockdown period. In column (2), where *EDF* is the dependent variable, the coefficient of the interaction term *Norway×Lockdown* is positive and statistically significant, suggesting that Norwegian firms are subject to a higher degree of expected default frequency (*EDF*) in the face of the national lockdown. The magnitude of this coefficient suggests that Norwegian firms confronted a 61% increase in the average level of expected default frequency relative to their Swedish counterparts during the lockdown period. Overall, the difference-in-difference results corroborate the notion that the most stringent form of government response to COVID-19 (i.e., national lockdown) leads to a higher degree of corporate default risk.

[Insert Table 6 here]

4.5. Possible channels

The established association between the government responses to COVID-19 and corporate default risk prompts us to investigate possible channels through which the lockdown measures affect default risk. We follow the prior literature (e.g., Landsman, Maydew, and Thornock, 2012; Lang, Lins, and Maffett, 2012; DeFond, Lim, and Zang, 2016; Pham, Merkoulova, and Veld, 2021) and conduct path analysis to test whether lower profitability, cash reserves, and inability to pay suppliers or creditors channel the adverse effects of the lockdown measures into corporate default risk. We report the results for these tests in Table 7.

The path coefficient β_1 is the magnitude of the direct path from government responses to COVID-19 to default risk. The path coefficient β_2 (β_3, β_4) is the magnitude of the path from profitability (account payable; cash holding) to default risk. The path coefficient $\hat{\alpha}_1 \times \widehat{\beta_2}$ ($\hat{\sigma}_1 \times \widehat{\beta_3}$; $\hat{\mu}_1 \times \widehat{\beta_4}$) is the magnitude of the indirect path from government responses to COVID-19 to default risk mediated through profitability (account payable; cash holding). The significance of the indirect effect is estimated using Sobel's (1982) test statistics. The results of Table 7 suggest that profitability reduction is a significant channel that helps explain 11.55% (14.12%) of the association between GSI and default risk as measured by distance-to-default (expected default frequency).

Similarly, Panel B's results suggest that cash reserve and account payable are other significant channels that help explain 1.84% and 11.43% of the relation between government responses to heath pandemic and corporate default. Overall, results from Table 7 suggest that government responses to COVID-19 not only exacerbate corporate default risk directly by interrupting access to capital markets but also in an indirect way by causing material declines in demand for products and services, as well as depleting firm liquidity.

[Insert Table 7 here]

[Insert Figure 1 here]

4.6. Differential Effects of Government Response Stringency

So as to conduct a comprehensive investigation of the roles of government response stringency, we investigate whether high and low government response stringency carry differential effects on corporate default risk over time when facing the same level of COVID-19 severity. To perform this time-series analysis, we first sort countries in our study sample into two groups of high and low COVID-19 severity.[9] Within each group of countries with high and low COVID-19 severity, we conduct a median split based on the degree of government response stringency. We are interested in two groups of countries, both facing a high level of COVID-19 severity but adopting contrasting degrees of government response stringency (i.e., high or low response stringency). Table 8 reports the regression estimates of *GSI* value in March 2020 from April 2020 to June 2020 for two subsamples of countries that implement relatively contrasting approaches to the pandemic while facing a similarly high level of COVID-19 severity.[10]

In columns (1) to (3) of Table 8 Panel A, we find that firms in countries imposing the strictest responses to curb the spread of COVID-19 in March 2020 first experienced a significant decrease in the distance-to-default (*DTD*) in April. However, the results suggest a reversal in the effect of stringent government responses in later months, indicating that the firm's average distance-to-default in May and June 2020 increases due to more COVID-19 restrictions implemented in March 2020. Similar evidence is obtained in Panel A columns (4) to (6). Specifically, we find that firms in countries with more stringent government responses in March 2020 experienced higher expected default frequency in April 2020. However, there is insufficient evidence regarding the significant impact of March 2020 strict policy responses to COVID-19 on expected default frequency in May and June 2020. Collectively, these results suggest that, while highly stringent policy responses to the pandemic trigger an immediate increase in corporate default risk in the following month, this effect is likely to disappear and, to some extent, even reverses in the later months.

[9] The classification is based on the median of the distribution regarding the country-level ratio of the monthly increase in the number of confirmed COVID-19 cases to the population for March 2020.
[10] We also conduct regression analyses based on firms in countries with less severe COVID-19 conditions. We report the results for this test in Appendix A3. Overall, we find no consistent patterns for countries with less severe COVID-19 conditions.

Table 8 Panel B examines the effect of lenient government responses to the pandemic on corporate default risk. In columns (1) to (3), we do not find significant evidence regarding the effect of lenient policy responses to COVID-19 implemented in March 2020 on firms' distance-to-default in the following months. In Panel B column (4), the positive association between government response stringency and expected default frequency is not statistically significant. Panel B column (5) results indicate a significant negative association between March 2020 lenient government responses to COVID-19 and expected default frequency. More strikingly, in column (6), we observe a reversal of the March 2020 effect, where firms from countries implementing lenient COVID-19 responses experience a higher level of corporate default risk in June 2020. Taken together, Panel B suggests that, although tolerant COVID-19 reactions do not affect corporate default risk in the subsequent month, they may cause firms to experience a higher level of default risk in the later periods. Collectively, the results from Table 8 corroborate Hypothesis H3.

[Insert Table 8 here]

4.7. Credit Default Swaps

Bharath and Shumway (2008) suggest that Merton's DTD model is a valuable tool to forecast default, but it does not produce a sufficient statistic to capture the probability of default. In the final test, we use credit default swap (CDS) spread (*CDS_Spread*) as a market-based indicator of default risk to validate our empirical findings.

The CDS spread represents the cost per annum that the CDS buyer pays the CDS seller for insurance against a reference entity's default. An increase in the default risk of the reference entity makes it more costly for the buyer to get insured. Therefore, one would expect the CDS spread to increase with the probability of default. We obtain the daily CDS composite spread from the Markit CDS pricing database. Following Zhang, Zhou, and Zhu (2009) and Loon and Zhong (2014), we use five-year CDS spreads as these contracts are the most liquid ones and provide the most reasonable pricing of default risk of the underlying assets (Pham, 2021). We aggregate the data to the monthly level by taking the average composite spread of all CDS instruments traded in a given month. The merging of the Markit data leaves us with 7,241 firm-month observations due to the limited coverage of the CDS market. We then re-estimate the univariate and regression analyses in Table 2, with *CDS_Spread* being the dependent variable. We report the results for these tests in Table 9.

In Panel A of the table, we document a significantly higher CDS spread among firms in countries with the most stringent preventive measures than those in the least restrictive ones over the first six months of 2020. There existed no significant difference between the two groups of firms during the six months before the pandemic. Consistent with this observation, the regression results provide evidence of a statistically significant positive association between *GSI* and *CDS_Spread*. These results suggest that investors are willing to pay a higher price to get themselves insured against firms facing more stringent COVID-19 measures, reaffirming the findings of our baseline analyses.

[Insert Table 9 here]

5. Conclusion

Unlike any other crises that the world has witnessed since the start of the 21st century, the COVID-19 pandemic imposes a huge challenge for policymakers worldwide as they need to balance the measures required to protect the community's well-being and actions to protect the health of the economy. In this study, we find that the cost of putting human health as the priority could lead to an increased risk of corporate default in the short run. However, such negative impacts of government responses to the pandemic have long-term benefits, as they help firms build better immune to insolvency risks in later periods. In countries where extreme lockdown measures are necessary, we also document that immediate and intense actions to contain the virus's impact can help firms encounter lower default risks. Economic supports from the government and social trust also show their effectiveness in relieving the pressure on firms' insolvency created by stringent lockdown measures. Our study contributes to the heated debate on how government should respond in cases of extreme events. Based on a universe of firms across 107 countries, this paper provides extensive empirical evidence to support the prediction that "*to save the economy, save people first*" (Alvelda, Ferguson, and Mallery, 2020).

Using the 2020 pandemic setting, we extend the emerging stream of extreme context research (ECR hereafter) that has been of great interest to practitioners, academic scholars, and policymakers. The ECR approach is particularly relevant for economic and business analysis as international business is "exposed more than any other management domain to the multiple tensions of changes in geographical, political, sociological, cultural and business environments" (Andriani and McKelvey, 2007: p.1226-1227). Furthermore, future studies can look at other macroeconomic and institutional factors that affect firm-level insolvency in an international context as an implication of our work. This topic has drawn increasing attention in recent global stress and uncertainty periods.

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Figure A1
Media mentions

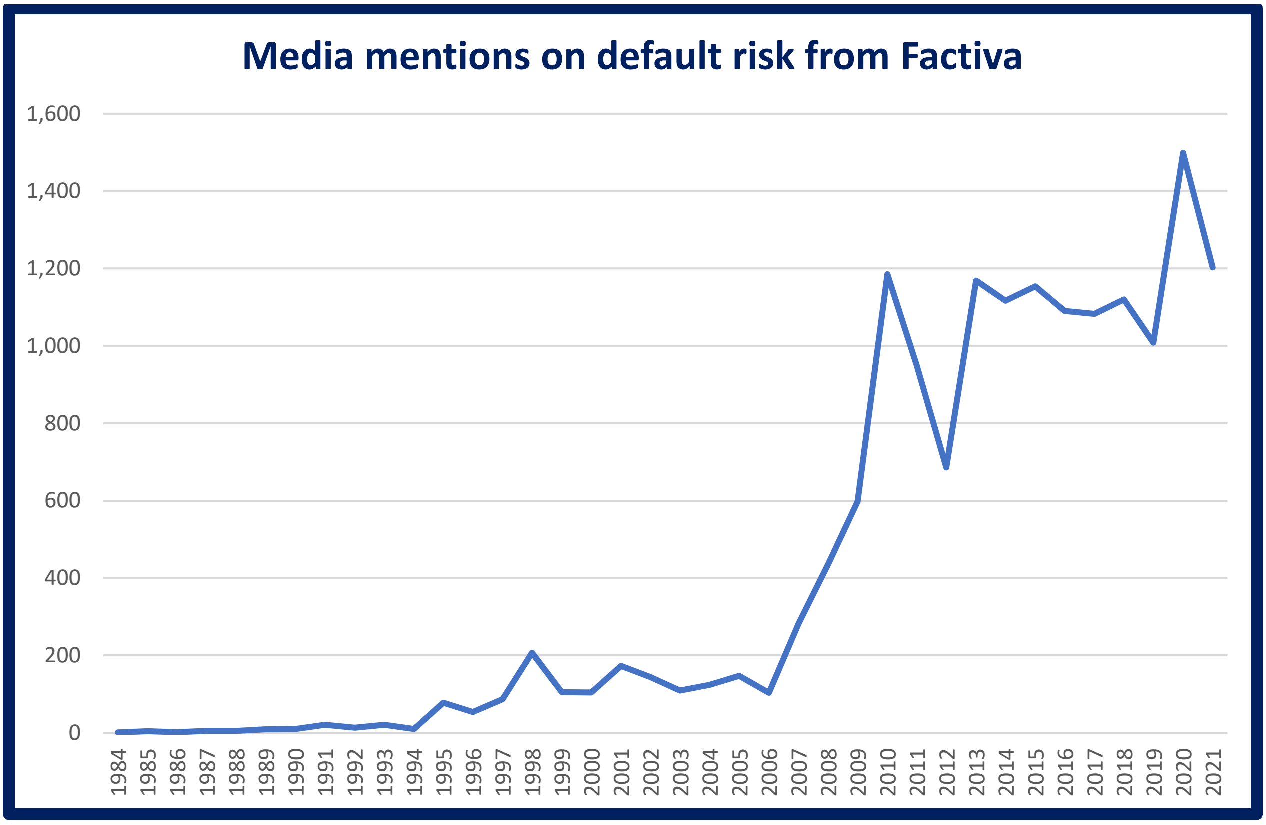
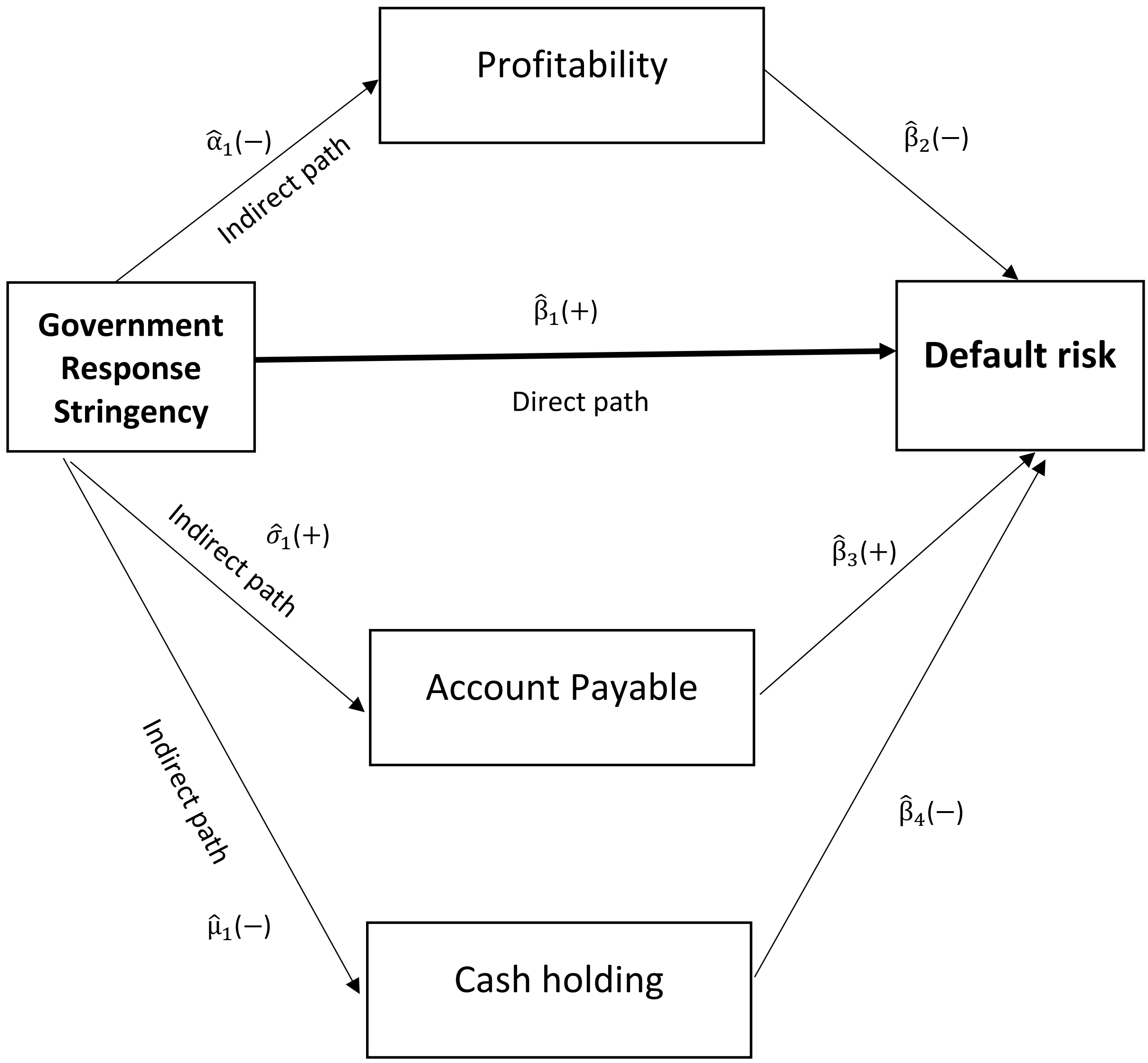


Figure A1 reports the number of media mentions on "corporate default", "default risk", or "insolvency risk" from Factiva over the period of January 1984 to December 2021.

Figure A2
Path Analysis



The figure depicts the direct and indirect path through which government response stringency can affect firm default risk. We estimate the following models in the path analysis:

(i) *Firm Default* = $\beta_0 + \beta_1\times$ *GSI* + $\beta_2\times$*Profitability* + $\beta_3\times$*Account Payable* + $\beta_4\times$ *Cash Holding* + *Controls* + Ɛ
(ii) *Profitability* = $\alpha_0 + \alpha_1\times$*GSI* + Ɛ
(iii) *Account Payable* = $\sigma_0 + \sigma_1\times$*GSI* + Ɛ
(iv) *Cash Holding* = $\mu_0 + \mu_1\times$*GSI* + Ɛ

The independent variable of interest is government response stringency (GSI). *Controls* are relevant control variables from the baseline regression in Table 2. The path coefficient β_1 is the magnitude of the direct path from GSI to corporate default. The path coefficient β_2, β_3, *and* β_4 are the magnitude of the path from profitability, account payable, and cash holding to corporate innovation, respectively. The path coefficient $\hat{\alpha}_1 \times \widehat{\beta_2}, \hat{\mu}_1 \times \widehat{\beta_3}$, $\hat{\mu}_1 \times \widehat{\beta_3}$ are the magnitude of the indirect path from GSI to corporate default mediated through profitability, account payable, and cash holding, respectively.

Table 1. Summary statistics for all variables and correlation matrix

The table reports the descriptive statistics (Panel A) and correlation matrix (Panel B) for the sample covering 21,978 firms across 107 countries/regions. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Appendix 1 provides detailed descriptions of the variables.

Panel A: Descriptive Statistics

Variable	Obs.	Mean	Std	25th pct	Median	75th pct
DTD	246,454	3.970	2.743	2.059	3.480	5.311
EDF	246,454	0.051	0.133	0.000	0.000	0.020
GSI	246,454	18.811	29.567	0.000	0.000	36.633
Size	246,454	7.706	3.020	5.698	7.609	9.374
Cash	246,454	0.176	0.186	0.047	0.113	0.236
Profitability	246,454	0.008	0.053	0.001	0.016	0.032
Leverage	246,454	0.222	0.208	0.025	0.187	0.355
Return	246,454	-0.016	0.154	-0.083	-0.021	0.043
Illiquidity	246,454	1.051	5.971	0.000	0.001	0.031

Panel B: Correlation Coefficient

	DTD	*EDF*	*GSI*	*Size*	*Cash*	*Profitability*	*Leverage*	*Return*
EDF	-0.495							
GSI	-0.122	0.033						
Size	0.090	-0.102	0.020					
Cash	0.155	-0.127	0.030	-0.207				
Profitability	0.251	-0.162	-0.020	0.346	-0.332			
Leverage	-0.308	0.269	0.000	0.158	-0.323	0.063		
Return	0.052	-0.065	0.078	0.010	0.031	0.019	-0.016	
Illiquidity	-0.151	0.215	0.000	-0.218	-0.019	-0.082	-0.005	0.002

Table 2. The Stringency of Government Responses and Default Risk

The table reports the results of the relation between government response stringency and default risk. Panel A and Panel B report the univariate and regression analysis results, respectively. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Robust standard errors are corrected for heteroskedasticity and clustered in both firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Univariate Test

	2019		2020	
	(1)	(2)	(3)	(4)
GSI Quintiles	*DTD*	*EDF*	*DTD*	*EDF*
1 (least stringent)	4.360	0.041	4.393	0.044
2	3.966	0.056	3.398	0.073
3	4.465	0.038	3.545	0.054
4	4.265	0.041	3.222	0.06
5 (most stringent)	4.408	0.038	3.747	0.048
(5) - (1)	0.048*	-0.003***	-0.646***	0.004***
p-value	(0.054)	(0.009)	(0.000)	(0.001)

Panel B: Regression Analyses

Variable	(1) *DTD*	(2) *DTD*	(3) *DTD*	(4) *EDF*	(5) *EDF*	(6) *EDF*
GSI	-0.0114***	-0.0069***	-0.0068***	0.0001***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size		0.1847***	0.1970***		-0.0076***	-0.0082***
		(0.000)	(0.000)		(0.000)	(0.000)
Cash		2.6058***	2.1891***		-0.0760***	-0.0673***
		(0.000)	(0.000)		(0.000)	(0.000)
Profitability		13.5802***	13.6751***		-0.4072***	-0.4185***
		(0.000)	(0.000)		(0.000)	(0.000)
Leverage		-4.0554***	-4.4369***		0.1706***	0.1728***
		(0.000)	(0.000)		(0.000)	(0.000)
Return		0.8240***	0.7536***		-0.0505***	-0.0476***
		(0.000)	(0.000)		(0.000)	(0.000)
Illiquidity		-0.0438***	-0.0412***		0.0038***	0.0037***
		(0.000)	(0.000)		(0.000)	(0.000)
Observations	246,454	246,454	246,454	246,454	246,454	246,454
Adjusted R-squared	0.015	0.310	0.349	0.001	0.220	0.234
Country fixed effects	No	Yes	Yes	No	Yes	Yes
Industry fixed effects	No	No	Yes	No	No	Yes
Year-Quarter fixed effects	No	Yes	Yes	No	Yes	Yes

Table 3. Government Response and Corporate Default: Individual Measures

The table reports the results of the relation between each of the nine metrics of the government response stringency and corporate default. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. Robust standard errors are corrected for heteroskedasticity and clustered in firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides a variable description. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: DTD as Corporate Default Measure

Variable	(1) *DTD*	(2) *DTD*	(3) *DTD*	(4) *DTD*	(5) *DTD*	(6) *DTD*	(7) *DTD*	(8) *DTD*	(9) *DTD*	(10) *DTD*
Movement restrictions	-0.1281***									-2.4134***
	(0.000)									(0.000)
International travel control		-0.2315***								-0.7336***
		(0.000)								(0.000)
Public information campaigns			-0.3430***							-1.4104***
			(0.000)							(0.000)
Cancel public events				-0.1643***						-5.2589***
				(0.000)						(0.000)
Gathering restrictions					-0.0257***					-1.1410***
					(0.000)					(0.000)
Close public transport						-0.0518***				-0.8722***
						(0.000)				(0.000)
School closures							-0.1026***			-2.1617***
							(0.000)			(0.000)
Stay at home								-0.0092***		-1.7339***
								(0.283)		(0.000)
Workplace closures									-0.0734***	-2.6475***
									(0.000)	(0.000)
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	246,454	246,454	246,454	246,454	246,454	246,454	246,454	246,454	246,454	246,454
Adjusted R-squared	0.348	0.35	0.351	0.348	0.348	0.348	0.348	0.348	0.348	0.352

Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: EDF as Corporate Default Measure

Variable	(1) *EDF*	(2) *EDF*	(3) *EDF*	(4) *EDF*	(5) *EDF*	(6) *EDF*	(7) *EDF*	(8) *EDF*	(9) *EDF*	(10) *EDF*
Movement restrictions	0.0021***									0.0681***
	(0.001)									(0.000)
International travel controls		0.0060***								0.0217***
		(0.000)								(0.000)
Public information campaigns			0.0082***							0.0401***
			(0.000)							(0.000)
Cancel public events				0.0052***						0.1663***
				(0.000)						(0.000)
Gathering restrictions					0.0010***					0.0368***
					(0.000)					(0.000)
Close public transport						-0.0006				0.0206***
						(0.356)				(0.000)
School closures							0.0030***			0.0678***
							(0.000)			(0.000)
Stay at home								0.0004		0.0563***
								(0.307)		(0.000)
Workplace closures									0.0020***	0.0824***
									(0.000)	(0.000)
All controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	246,454	246,454	246,454	246,454	246,454	246,454	246,454	246,454	246,454	246,454
Adjusted R-squared	0.234	0.235	0.235	0.234	0.234	0.234	0.234	0.234	0.234	0.235
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. COVID-19 Severity

The table reports the estimates of the relationship between government response stringency and corporate default conditional on COVID-19 severity. Control variables are similar to Table 2 and are collapsed for brevity. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Robust standard errors are corrected for heteroskedasticity and clustered in both firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: COVID-19 Severity

Variable	(1) *DTD*	(2) *DTD*	(3) *EDF*	(4) *EDF*
GSI × COVID-19 Cases	0.0743***		-0.0018***	
	(0.000)		(0.000)	
COVID-19 Cases	-7.8771***		0.1488***	
	(0.000)		(0.000)	
GSI × COVID-19 Deaths		0.2872***		-0.0063*
		(0.000)		(0.074)
COVID-19 Deaths		-62.2710***		0.9065***
		(0.000)		(0.000)
GSI	-0.0088***	-0.0079***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Control Variables	Yes	Yes	Yes	Yes
Observations	246,454	246,454	246,454	246,454
Adjusted R-squared	0.353	0.351	0.235	0.235
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year-Quarter fixed effects	Yes	Yes	Yes	Yes

Panel B. Industry Exposure and Corporate Default

Variable	(1) *DTD*	(2) *EDF*
GSI × Industry At Risk	-0.0026***	0.0001**
	(0.001)	(0.024)
Industry At Risk	-0.0453	0.0099***
	(0.175)	(0.000)
GSI	-0.0067***	0.0002***
	(0.000)	(0.000)
All controls included	Yes	Yes
Observations	246,454	246,454
Adjusted R-squared	0.310	0.221

Country fixed effects	Yes	Yes
Industry fixed effects	No	No
Year-Quarter fixed effects	Yes	Yes

Table 5. Government Support, Creditor Protection, and Social Trust

The table reports the regression estimates of the relationship between government response stringency and corporate default conditional on COVID-19 government support (Panel A), creditor protection (Panel B), and social trust (Panel C). *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Control variables are similar to Table 2 and are collapsed for brevity. Robust standard errors are corrected for heteroskedasticity and clustered in both firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Government Supports during COVID-19

Variable	(1) *DTD*	(2) *DTD*	(3) *EDF*	(4) *EDF*
GSI × Debt Relief	0.0068***		-0.0002***	
	(0.000)		(0.000)	
Debt Relief	-0.6916***		0.0192***	
	(0.000)		(0.000)	
GSI × Income Support		0.0034***		-0.0001***
		(0.000)		(0.001)
Income Support		-0.4240***		0.0119***
		(0.000)		(0.000)
GSI	-0.0073***	-0.0065***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Control Variables	Yes	Yes	Yes	Yes
Observations	246,454	246,454	246,454	246454
Adjusted R-squared	0.350	0.349	0.235	0.235
Country fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year-Quarter fixed effects	Yes	Yes	Yes	Yes

Panel B: Creditor Protection

Variable	(1) *DTD*	(2) *DTD*	(3) *EDF*	(4) *EDF*
GSI × Recovery	-0.0002***		0.0000***	
	(0.000)		(0.000)	
Recovery	0.0056***		-0.0002***	
	(0.000)		(0.000)	
GSI × RFI		-0.0186***		0.0004***
		(0.000)		(0.000)
RFI		0.0371		0.0067***
		(0.249)		(0.000)

GSI	-0.0013**	-0.0082***	-0.0001	0.0002***
	(0.038)	(0.000)	(0.135)	(0.000)
Control Variables	Yes	Yes	Yes	Yes
Observations	246,454	246,454	246,454	246,454
Adjusted R-squared	0.276	0.278	0.192	0.193
Country fixed effects	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes
Year-Quarter fixed effects	Yes	Yes	Yes	Yes

Panel C: Social Trust

Variable	(1) DTD	(2) DTD	(3) EDF	(4) EDF
GSI × Government Trust	0.0126***		-0.0001*	
	(0.000)		(0.055)	
Government Trust	0.5949***		-0.0376***	
	(0.000)		(0.000)	
GSI × Trust Others		0.0026***		-0.0000
		(0.000)		(0.180)
Trust Others		0.0777***		-0.0062***
		(0.000)		(0.000)
GSI	-0.0126***	-0.0183***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.001)
Control Variables	Yes	Yes	Yes	Yes
Observations	203,761	198,859	203,761	198,859
Adjusted R-squared	0.274	0.271	0.171	0.166
Country fixed effects	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes
Year-Quarter fixed effects	Yes	Yes	Yes	Yes

Table 6. Addressing Endogeneity Issues

Panel A reports the relation between government response stringency and default risk when firm fixed effects are employed (Columns 1-2) and when the entropy balancing approach is adopted (Columns 3-4). Panel B reports the results using a difference-in-differences approach to investigate a pair of neighboring countries that adopt different strategies to handle the pandemic. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Control variables are similar to Table 2 and are collapsed for brevity. Robust standard errors are corrected for heteroskedasticity and clustered in both firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative Identifications

	Firm-Fixed Effects		Entropy Balanced Sample	
	(1)	(2)	(3)	(4)
Variable	*DTD*	*EDF*	*DTD*	*EDF*
GSI	-0.0057***	0.0001***	-0.009***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.6617***	-0.0033	0.143***	-0.008***
	(0.000)	(0.284)	(0.000)	(0.000)
Cash	0.0558	-0.0108**	2.026***	-0.071***
	(0.423)	(0.011)	(0.000)	(0.000)
Profitability	0.9112***	-0.0373***	12.086***	-0.439***
	(0.000)	(0.001)	(0.000)	(0.000)
Leverage	-1.1692***	0.0658***	-4.179***	0.194***
	(0.000)	(0.000)	(0.000)	(0.000)
Return	0.4819***	-0.0285***	0.334***	-0.031***
	(0.000)	(0.000)	(0.000)	(0.000)
Illiquidity	-0.0016***	0.0002***	-0.038***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	246,454	246,454	123,328	123,328
Adjusted R-squared	0.884	0.871	0.353	0.264
Country fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-Quarter fixed effects	Yes	Yes	Yes	Yes

Panel B: Difference-in-Differences

	(1)	(2)
Variable	*DTD*	*EDF*
Norway	0.1490	0.0043
	(0.287)	(0.596)
Lockdown	-0.3268***	-0.0041
	(0.000)	(0.293)

Norway × Lockdown	-0.2677*	0.0310***
	(0.061)	(0.001)
Size	0.3864***	-0.0190***
	(0.000)	(0.000)
Cash	1.6853***	-0.0714***
	(0.000)	(0.000)
Profitability	8.6777***	-0.3043***
	(0.000)	(0.000)
Leverage	-2.6551***	0.1428***
	(0.000)	(0.000)
Return	0.6063***	-0.0715***
	(0.004)	(0.000)
Illiquidity	-0.0189***	-0.0002
	(0.000)	(0.720)
Observations	2,621	2,621
Adjusted R-squared	0.403	0.291
Country fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year-Quarter fixed effects	Yes	Yes

Table 7. Path Analysis Regressions

Path analysis reports the direct and indirect path through which government response stringency can affect default risk. Figure A1 presents model specifications and a graphical illustration of the path analysis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent Variable = DTD

	Path = Profitability		**Path = Cash**		**Path = A/Payable**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Direct Path						
P (GSI, DTD)	-0.0056***	(0.000)	-0.0064***	(0.000)	-0.0065***	(0.000)
Indirect Path						
P (GSI, Path)	-0.0055***	(0.000)	0.0000***	(0.000)	0.0021***	(0.000)
P (Path, DTD)	0.1331***	(0.000)	2.8072***	(0.000)	-0.1384***	(0.000)
P (GSI, Path) × P (Path, DTD)	-0.0007***	(0.000)	-0.0001***	(0.000)	-0.0003***	(0.000)
Total effect	-0.0063***	(0.000)	-0.0066**	(0.041)	-0.0068***	(0.000)
Mediated % in Total	11.55%		1.88%		4.26%	
Observations	246,454		246,454		218,554	

Panel B: Dependent Variable = EDF

	Path = Profitability		**Path = Cash**		**Path = A/Payable**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Direct Path						
P (GSI, EDF)	0.0001***	(0.000)	0.0002***	(0.000)	0.0001***	(0.000)
Indirect Path						
P (GSI, Path)	-0.0055***	(0.000)	0.0000***	(0.000)	0.0021***	(0.000)
P (Path, EDF)	-0.0038***	(0.000)	-0.0642***	(0.000)	0.0085***	(0.000)
P (GSI, Path) × P (Path, EDF)	0.0000***	(0.000)	0.0000***	(0.000)	0.0000***	(0.000)
Total effect	0.0001***	(0.000)	0.0002**	(0.041)	0.0002***	(0.000)
Mediated % in Total	14.12%		1.84%		11.43%	
Observations	246,454		246,454		218,554	

Table 8. Regression Analyses for Firms in Countries with Severe COVID-19 Conditions

The table reports the regression estimates of the relation between different levels of government response stringency and default risk over time for countries with high exposure to COVID-19. High and low response stringency levels are based on the sample median of the government response stringency measure. High and low exposure to COVID-19 is based on the sample median of the country-level ratio of the monthly increase in the number of confirmed COVID-19 cases to the population in March 2020. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Control variables are similar to Table 2 and are collapsed for brevity. Robust standard errors are corrected for heteroskedasticity and clustered in both firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: High Level of COVID-19 Response Stringency in Countries with High Exposure to COVID-19

	April 2020	May 2020	June 2020	April 2020	May 2020	June 2020
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	DTD	DTD	DTD	EDF	EDF	EDF
GSI	-0.4745***	0.0525***	0.0590***	0.0137***	-0.0008	-0.0015
	(0.000)	(0.000)	(0.000)	(0.003)	(0.368)	(0.136)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,397	4,382	4,374	4,397	4,382	4,374
Adjusted R-squared	0.326	0.290	0.301	0.270	0.242	0.264
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Low Level of COVID-19 Response Stringency in Countries with High Exposure to COVID-19

	April 2020	May 2020	June 2020	April 2020	May 2020	June 2020
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	DTD	DTD	DTD	EDF	EDF	EDF
GSI	-0.0458	0.0248	-0.0131	0.0004	-0.0042***	0.0021***
	(0.112)	(0.343)	(0.494)	(0.852)	(0.000)	(0.006)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,582	4,546	4,576	4,582	4,546	4,576
Adjusted R-squared	0.492	0.417	0.441	0.298	0.261	0.258
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Credit Default Swaps

The table reports the results of the relation between government response stringency and default risk, proxied by the CDS spread (*CDS_Spread*). Panels A and B report the univariate and regression analysis results, respectively. *CDS_Spread* is the monthly average composite spread of all 5-year CDS instruments traded in a given month for a given firm. Robust standard errors are corrected for heteroskedasticity and clustered in both firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Univariate Test

	2019	2020
GSI Quintiles	*CDS_Spread*	*CDS_Spread*
1 (least stringent)	0.014	0.013
2	0.013	0.019
3	0.013	0.025
4	0.013	0.026
5 (most stringent)	0.013	0.024
(5) - (1)	-0.001	0.011
p-value	0.4404	0.0012

Panel B: Regression Analysis

	(1)	(2)	(3)
Variable	CDS_Spread	CDS_Spread	CDS_Spread
GSI	0.0001**	0.0001*	0.0001*
	(0.010)	(0.050)	(0.053)
Size		-0.0070***	-0.0071***
		(0.000)	(0.000)
Cash		-0.0116	-0.0213**
		(0.140)	(0.015)
Profitability		-0.3728***	-0.3049***
		(0.000)	(0.001)
Leverage		0.0471***	0.0564***
		(0.000)	(0.000)
Return		0.0093	0.0132
		(0.763)	(0.677)
Illiquidity		0.0391***	0.0334***
		(0.002)	(0.003)
Observations	7,241	7,241	7,241
Adjusted R-squared	0.003	0.054	0.072
Country fixed effects	No	Yes	Yes
Industry fixed effects	No	No	Yes
Quarter-Year FE	No	Yes	Yes

Appendix 1. Variable Description

Variables		
Default Risk Measures		
DTD	Merton (1974)'s distance-to-default, measured based on Duan et al. (2012)'s approach for multiperiod default prediction. The larger the value, the lower the probability of default.	Credit Research Initiative
EDF	Expected default frequency, which is calculated as the cumulative normal distribution of the negative distance-to-default.	Credit Research Initiative, Authors' calculation
Government Responses to COVID-19		
GSI	A country-level measure of COVID-19 government response stringency. The index is constructed based on nine different metrics including restrictions on internal movement, international travel controls, public information campaigns, cancellation of public events, restrictions on public gatherings, public transport closures, school closures, stay-at-home orders, and workplace closures.	Hale et al. (2020)
Movement restrictions	Restrictions on internal movement.	Hale et al. (2020)
International travel controls	Restrictions on international travel.	Hale et al. (2020)
Public information campaigns	Presence of public information campaigns about COVID-19.	Hale et al. (2020)
Cancel public events	Cancellation of public events.	Hale et al. (2020)
Gathering restrictions	The cut-off size for bans on gatherings.	Hale et al. (2020)
Close public transport	Closing of public transport.	Hale et al. (2020)
School closures	closings of schools and universities	Hale et al. (2020)
Stay at home	Orders to "shelter-in- place" and otherwise confine to home.	Hale et al. (2020)
Workplace closures	Closings of workplaces.	Hale et al. (2020)
Control Variables		
Size	The natural logarithm of total assets	Compustat
Cash	Cash-to-asset ratio	Compustat
Profitability	Return on asset	Compustat
Leverage	Book value of debt to asset	Compustat

Return	Monthly excess return, which is computed as the difference between firm stock return and market return over the same period.	Compustat and CRSP
Illiquidity	Amihud's (2002) measure of illiquidity.	Compustat and CRSP
Other Variables		
COVID-19 Cases	For each country, the monthly increase in the number of confirmed positive COVID-19 cases scaled by the country's population.	Johns Hopkins University
COVID-19 Deaths	For each country, the monthly increase in the number of COVID-19 deaths scaled by the country's population.	Johns Hopkins University
Income Support	Income support for people who lose their jobs or cannot work.	Hale et al. (2020)
Debt Relief	Freezing financial obligations for both households and firms.	Hale et al. (2020)
Recovery	Creditors' recovery rate. A higher value of recovery rate indicates a lower expected loss and a shorter time for a creditor to get paid in the event of default.	Djankov et al. (2008)
RFI	Renegotiation failure index, which summarizes the legal characteristics that protect debtholders from shareholders' strategic default; a higher value of *RFI* suggests stronger protection of creditors' rights.	Djankov et al. (2008)
Government Trust	Country-level public trust in the government.	Falk et al. (2018)
Trust Others	People's trust in other members from the same society.	World Value Survey
Norway	An indicator variable takes the value of 1 for firms located in Norway and 0 otherwise.	Compustat
Lockdown	An indicator variable takes the value of 1 for both Norwegian and Swedish firms from March 2020 to April 2020 and 0 otherwise.	Compustat
A/Payable	Account payable days, which is computed as the ratio of accounts payables to daily cost of goods sold.	Compustat
Industry At Risk	An indicator variable takes the value of 1 for firms from five industries most impacted by COVID-19 and 0 otherwise	S&P Global Market Intelligence
CDS_Spread	CDS spread obtained from Markit CDS pricing database	Markit CDS database

Appendix 2. Summary Statistics by Country/Region

The table reports the summary statistics for each country/region in the sample. Our sample includes 21,978 firms across 107 countries/regions. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Appendix 1 provides detailed descriptions of the variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Difference	
Country/Region	Observations	#Firms	GSI (2020)	DTD (2020)	EDF (2020)	DTD (2019)	EDF (2019)	(4) - (6)	(5) - (7)
Argentina	612	54	42.46	1.046	0.247	0.622	0.350	0.424	-0.102
Australia	12,255	1,201	33.16	2.725	0.081	3.450	0.060	-0.725	0.021
Austria	478	45	33.13	3.962	0.030	5.165	0.010	-1.203	0.020
Azerbaijan	12	1	37.73	3.158	0.002	4.338	0.000	-1.180	0.002
Bahrain	73	9	36.81	7.328	0.004	6.650	0.002	0.678	0.002
Bangladesh	1,636	161	39.92	3.817	0.028	4.260	0.027	-0.443	0.001
Barbados	6	1	0.00	-	-	6.044	0.000	-	-
Belgium	833	75	36.54	3.986	0.036	4.634	0.029	-0.648	0.007
Bermuda	34	5	36.32	2.556	0.078	3.559	0.065	-1.003	0.013
Botswana	60	6	36.12	10.925	0.001	11.801	0.001	-0.876	0.000
Brazil	2,072	184	34.27	2.810	0.137	3.652	0.122	-0.842	0.016
British Virgin Islands	27	4	28.53	2.838	0.037	3.379	0.017	-0.541	0.020
Bulgaria	320	30	31.62	4.326	0.131	4.458	0.093	-0.131	0.038
Cambodia	12	1	24.96	7.065	0.000	8.826	0.000	-1.760	0.000
Cayman Islands	57	6	37.72	5.097	0.010	5.171	0.015	-0.074	-0.005
Chile	971	87	30.40	4.667	0.018	6.287	0.008	-1.620	0.010
China	45,329	3,911	52.17	4.538	0.018	4.535	0.015	0.003	0.003

Colombia	194	18	38.38	3.428	0.036	4.273	0.035	-0.845	0.002
Croatia	509	46	38.91	3.816	0.120	4.455	0.136	-0.639	-0.016
Cyprus	226	24	37.70	3.913	0.076	4.537	0.069	-0.624	0.007
Czech Republic	108	10	33.37	6.030	0.002	7.699	0.000	-1.669	0.002
Denmark	1,133	103	31.33	4.478	0.026	5.210	0.028	-0.732	-0.002
Egypt	1,441	131	32.87	2.896	0.083	3.204	0.072	-0.308	0.011
Estonia	156	14	28.52	5.033	0.081	5.640	0.072	-0.606	0.009
Faroe Islands	7	1	0.00	6.173	0.000	7.512	0.000	-1.339	0.000
Finland	1,395	127	29.02	4.221	0.027	4.654	0.025	-0.433	0.002
France	5,352	484	41.91	3.411	0.062	4.069	0.051	-0.658	0.011
French Guiana	7	1	0.00	0.427	0.335	1.047	0.149	-0.620	0.185
Gabon	12	1	35.00	4.219	0.000	5.099	0.000	-0.880	0.000
Georgia	12	1	45.74	-0.439	0.679	0.147	0.447	-0.586	0.231
Germany	4,511	396	33.51	3.632	0.050	4.315	0.038	-0.683	0.011
Ghana	44	5	28.71	3.719	0.015	3.107	0.040	0.611	-0.025
Gibraltar	32	4	34.86	1.560	0.239	2.256	0.166	-0.697	0.073
Greece	1,407	129	35.31	2.498	0.157	3.239	0.137	-0.740	0.019
Guernsey	50	10	0.00	6.457	0.021	6.724	0.028	-0.268	-0.007
Hong Kong	10,015	886	41.74	2.761	0.096	3.296	0.072	-0.535	0.024
Hungary	177	17	31.73	4.581	0.023	5.308	0.028	-0.726	-0.005
Iceland	123	12	25.68	4.625	0.039	4.269	0.036	0.356	0.003
India	1,660	194	41.29	2.905	0.107	3.453	0.075	-0.548	0.032
Indonesia	4,973	432	36.29	3.080	0.104	3.882	0.065	-0.802	0.039

Ireland	394	40	37.08	4.123	0.040	5.177	0.039	-1.054	0.001
Isle of Man	34	7	0.00	3.245	0.116	3.186	0.128	0.059	-0.012
Israel	2,983	264	40.53	3.592	0.049	4.375	0.040	-0.783	0.009
Italy	2,846	263	46.21	3.538	0.049	4.390	0.036	-0.852	0.013
Jamaica	230	22	39.69	3.297	0.013	3.773	0.005	-0.476	0.008
Japan	72	7	25.47	2.049	0.103	3.714	0.040	-1.664	0.063
Jersey	24	5	0.00	5.014	0.021	4.726	0.010	0.288	0.012
Jordan	711	70	38.53	4.174	0.035	4.069	0.037	0.105	-0.002
Kazakhstan	69	7	35.98	6.079	0.002	5.629	0.006	0.450	-0.004
Kenya	199	21	38.17	3.018	0.184	3.391	0.186	-0.373	-0.002
Kuwait	712	63	43.14	3.132	0.072	3.759	0.066	-0.627	0.006
Latvia	130	16	28.15	3.500	0.130	4.471	0.139	-0.971	-0.009
Lithuania	264	23	34.70	4.231	0.015	4.657	0.012	-0.426	0.003
Luxembourg	239	23	30.70	3.474	0.013	4.023	0.011	-0.549	0.003
Macao	60	6	30.46	4.138	0.001	4.465	0.001	-0.327	0.000
Malawi	24	3	24.44	3.296	0.008	3.810	0.003	-0.514	0.005
Malaysia	9,009	774	36.09	3.388	0.080	4.043	0.059	-0.655	0.021
Malta	99	16	0.00	5.959	0.014	6.116	0.009	-0.157	0.005
Mauritius	244	22	31.76	4.639	0.096	6.579	0.073	-1.940	0.023
Mexico	957	84	30.82	4.620	0.050	5.107	0.035	-0.487	0.015
Moldova	12	1	37.43	7.210	0.000	6.848	0.000	0.362	0.000
Monaco	7	1	0.00	8.189	0.000	6.764	0.000	1.425	0.000
Mongolia	24	3	44.86	1.742	0.144	2.291	0.057	-0.549	0.087

Morocco	496	46	39.21	4.201	0.049	4.520	0.045	-0.319	0.004
Mozambique	12	1	23.29	0.368	0.361	0.728	0.234	-0.360	0.126
Namibia	24	3	27.74	7.010	0.024	8.098	0.007	-1.088	0.018
Netherlands	934	83	32.67	3.865	0.050	4.791	0.038	-0.926	0.012
New Zealand	1,173	104	36.53	4.308	0.038	5.662	0.030	-1.354	0.008
Nigeria	864	78	34.44	2.538	0.155	2.697	0.175	-0.159	-0.020
Norway	1,535	137	31.83	2.942	0.115	3.362	0.086	-0.420	0.029
Oman	356	36	41.38	3.870	0.058	4.732	0.050	-0.863	0.008
Pakistan	1,631	151	41.06	2.738	0.089	2.775	0.102	-0.038	-0.012
Panama	28	4	39.28	1.044	0.404	1.623	0.381	-0.579	0.022
Papua New Guinea	12	1	30.17	2.223	0.013	2.390	0.010	-0.167	0.004
Peru	325	31	41.02	4.873	0.045	5.477	0.030	-0.604	0.015
Philippines	1,666	145	47.72	3.490	0.046	4.430	0.030	-0.940	0.016
Poland	3,950	343	35.60	2.686	0.095	2.967	0.090	-0.281	0.005
Portugal	372	35	36.44	2.718	0.160	3.312	0.142	-0.594	0.018
Qatar	250	23	38.57	6.246	0.001	7.088	0.001	-0.842	0.000
Romania	589	56	37.90	4.096	0.052	4.637	0.053	-0.541	-0.001
Russia	1,928	168	37.05	2.436	0.147	2.813	0.165	-0.377	-0.018
Réunion	7	1	0.00	1.290	0.099	1.999	0.047	-0.709	0.052
Saudi Arabia	1,501	128	41.22	5.698	0.007	6.755	0.004	-1.057	0.004
Serbia	120	13	38.98	5.605	0.073	7.015	0.032	-1.410	0.040
Singapore	4,552	418	38.22	2.820	0.138	3.393	0.119	-0.573	0.019
Slovakia	31	4	34.27	3.616	0.003	3.542	0.001	0.075	0.002

Slovenia	123	12	32.00	4.530	0.037	5.037	0.032	-0.507	0.004
South Africa	1,871	172	35.86	2.286	0.177	3.043	0.118	-0.757	0.059
South Korea	18,079	1,530	34.87	3.180	0.037	3.647	0.029	-0.467	0.008
Spain	1,147	105	37.83	3.678	0.044	4.594	0.043	-0.915	0.001
Sri Lanka	1,973	182	36.30	2.782	0.106	3.253	0.078	-0.471	0.028
Sudan	9	1	35.82	1.431	0.092	2.004	0.023	-0.573	0.069
Sweden	6,608	584	18.36	3.535	0.047	4.029	0.047	-0.495	0.000
Switzerland	1,832	162	32.04	5.442	0.022	6.101	0.019	-0.659	0.003
Taiwan	10,162	856	19.48	5.721	0.007	6.381	0.005	-0.660	0.001
Tanzania	39	5	19.76	5.094	0.004	2.922	0.015	2.171	-0.011
Thailand	6,382	547	31.19	4.295	0.033	5.768	0.019	-1.473	0.014
Tunisia	234	22	37.35	4.948	0.051	4.800	0.072	0.148	-0.021
Turkey	3,325	287	35.52	2.996	0.048	2.856	0.081	0.140	-0.032
Uganda	24	3	39.25	1.128	0.152	1.931	0.089	-0.803	0.063
Ukraine	139	13	38.26	1.573	0.242	1.962	0.207	-0.389	0.035
United Arab Emirates	377	35	35.04	2.860	0.127	3.632	0.057	-0.772	0.070
United Kingdom	9,463	862	33.96	3.555	0.059	4.484	0.039	-0.929	0.020
United States	41,162	3,687	32.75	3.455	0.062	4.437	0.042	-0.982	0.020
Venezuela	6	1	0.26	-0.238	0.594	-0.188	0.575	-0.050	0.020
Vietnam	3,457	334	41.93	3.401	0.055	3.872	0.053	-0.471	0.003
Zambia	12	1	22.73	2.010	0.025	2.138	0.018	-0.128	0.008
Total	**246,454**	**21,978**							
Average			31.805	3.757	0.082	4.309	0.066	-0.536***	0.015***

Appendix 3. Regression Analysis for Firms in Countries with Less Severe COVID-19 Conditions

The table reports the estimates of the relation between different levels of government response stringency and corporate default over time for countries with low exposure to COVID-19. High and low levels of response stringency are based on the sample median of the government response stringency measure. High and low exposure to COVID-19 is based on the sample median of the country-level ratio of the monthly increase in the number of confirmed COVID-19 cases to the population in March 2020. *DTD* is the distance-to-default measure. *EDF* refers to the expected default frequency. *GSI* is the government response stringency index. Control variables are similar to Table 2 and are collapsed for brevity. Robust standard errors are corrected for heteroskedasticity and clustered in firm and quarter dimensions (Petersen, 2009; Thompson, 2011). Coefficients are listed in the first row, and *p*-values are in parentheses. Appendix 1 provides the variable descriptions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: High Level of COVID-19 Response Stringency in Countries with Low Exposure to COVID-19

	April 2020	May 2020	June 2020	April 2020	May 2020	June 2020
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*DTD*	*DTD*	*DTD*	*EDF*	*EDF*	*EDF*
GSI	0.0235***	-0.0204***	0.0847***	-0.0030***	0.0026***	-0.0078***
	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.0830***	-0.1057***	-0.1032***	-0.0060***	-0.0065***	-0.0070***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	3.3327***	3.1306***	3.1096***	-0.0335***	-0.0280***	-0.0229***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.009)
Profitability	16.6067***	14.6726***	18.9102***	-0.5872***	-0.5393***	-0.4899***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-4.3823***	-4.8287***	-4.8597***	0.1112***	0.1196***	0.1119***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return	1.5647***	1.6246***	1.6113***	-0.0841***	-0.0439***	-0.0730***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
Illiquidity	-0.1248***	-0.1970***	-0.1619***	0.0136***	0.0143**	0.0090**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.037)	(0.022)

All controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,149	4,155	4,175	4,149	4,155	4,175
Adjusted R-squared	0.368	0.362	0.378	0.200	0.171	0.157
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Low Level of COVID-19 Response Stringency in Countries with Low Exposure to COVID-19

	April 2020	May 2020	June 2020	April 2020	May 2020	June 2020
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*DTD*	*DTD*	*DTD*	*EDF*	*EDF*	*EDF*
GSI	-0.0662***	-0.0297***	-0.0378***	0.0080***	0.0045***	0.0055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.0852***	0.0615***	0.0726***	-0.0057***	-0.0052***	-0.0055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	2.7361***	2.5473***	2.5180***	-0.0556***	-0.0478***	-0.0507***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	16.6173***	17.3654***	17.3300***	-1.0295***	-1.0727***	-0.9783***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-4.0666***	-4.1022***	-4.1562***	0.1899***	0.1899***	0.1823***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return	1.9713***	-1.5840***	-0.5316***	-0.0322**	-0.0089	-0.0191
	(0.000)	(0.000)	(0.000)	(0.032)	(0.468)	(0.179)
Illiquidity	-0.0325***	-0.0317***	-0.0368***	0.0032***	0.0020***	0.0028***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All controls	Yes	Yes	Yes	Yes	Yes	Yes

Observations	6,332	6,707	6,716	6,332	6,707	6,716
Adjusted R-squared	0.427	0.429	0.429	0.273	0.258	0.257
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes